International Journal of All Research Education and Scientific Methods (IJARESM),
ISSN: 2455-6211, Volume 13, Issue 5, May-2025, Available online at: www.ijaresm.com

Agro Multimodal Chatbot using CNN and RAG

Zarinabegam Mundargi[1], Shreenath Ubale[2], Tilaksingh Chauhan[3], Satyajit Shinde[4], Vallabh Wasule[5], Nidhish Wakodikar[6], Vaishnavi Shivade[7]

[1,2,3,4,5,6,7]Vishwakarma Institute of Technology, Pune, India

---

ABSTRACT

The Indian agricultural sector is known as an international powerhouse. It ranks second in producingfruits, vegetables, tea,wheat, cotton, rice, and sugarcane. In the agricultural sector, about 60% of the population of India is employed accounting for 17% of the country's GDP.Despite its critical importance,according to estimates, plant diseases cost India's crops more than INR 290 billion a year. Approximately 125 million tonnes of crops were destroyed by fungal diseases alone in 2012. The food supply, which is already an issue for 800 million underfed people, can be challenged by plant diseases. These crop diseases pose a threat to sustainable agriculture and food supply networks in addition to lowering efficiency. Artificial intelligence powered systems can evaluate textual and visual inputs to produce useful insights, even at remote locations. The Agro Multimodal Chatbot fills these gaps by combining advanced conversational AI with deep learning-based image processing. The chatbot uses Retrieval-Augmented Generation (RAG) to provide accurate, contextually appropriate answers to farmer enquiries and Convolutional Neural Networks (CNNs) to identify crop diseases in real-time from images. This chatbot offers practical agricultural guidance, treatment recommendations, and preventive measures in along with helping with the diagnosis of diseases. The chatbot is created to empower farmers, solve major agricultural problems, and open the door to a robust and sustainable farming ecosystem.

Keywords— Plant Disease Detection, Multimodal Chatbot, Convolutional Neural Networks (CNNs), Retrieval-Augmented Generation (RAG), Agricultural Automation.

INTRODUCTION

The foundation of human civilisation, agriculture is essential to maintaining livelihoods and guaranteeing food security. In addition to being a major force behind the Indian economy, the agriculture industry employs around 60% of the country's workforce. Agriculture accounts for over 17% of the country's GDP, and it is the second-largest producer of vital crops like rice, wheat, cotton, and sugarcane. Notwithstanding its importance, the industry continues to encounter obstacles such as low production, climate variability, and a lack of grassroots adoption of new technologies. Crop diseases are the most dangerous of all, resulting in losses of billions of rupees every year.

Crop diseases provide a significant challenge to attaining global food security in addition to being a financial burden. Plant diseases are estimated to cost India approximately INR 290 billion in lost harvests annually; in 2012, 125 million tonnes of crops were destroyed by fungal infections alone. Such extensive harm has far-reaching effects, endangering food supply networks and making the 800 million people who are currently undernourished in the world even more hungry. Innovative, scalable, and easily available solutions that are suited to farmers' needs are needed to address these issues.

Artificial intelligence (AI) developments in recent years have created new opportunities to address agricultural issues. Artificial intelligence (AI)-driven systems have proven their capacity to examine intricate information, identify trends, and offer useful insights. For farmers, however, current technologies frequently lack usability and accessibility, particularly in nations like India where language variety and technology illiteracy present major obstacles. In addition to being efficient, farmers require equipment that are easy to use, bilingual, and able to handle a variety of agricultural situations.

Our initiative fills this gap by introducing the Agro Multimodal Chatbot, a complete AI-powered system that gives farmers access to real-time agricultural assistance. The system combines two state-of-the-art technologies: Retrieval-Augmented Generation (RAG) to respond to text-based agricultural queries and Convolutional Neural Networks (CNNs) for image-based crop disease identification. Because of its multilingual capabilities, the chatbot can serve customers from a variety of language backgrounds in India. The Agro Multimodal Chatbot offers farmers disease diagnosis, treatment recommendations, preventive measures, and general agricultural help in their choice language by seamlessly integrating text and visual analysis.

This initiative sits at the nexus of grassroots agricultural demands and cutting-edge AI technologies. It makes use of technologies like cloud-based deployment, natural language processing, and deep learning to develop an intuitive platform that can be accessed from smartphones or other simple internet-enabled devices. The Agro Multimodal Chatbot hopes to revolutionise crop management and decision-making by tackling the technical and social aspects of agricultural issues, thereby fostering a more resilient and sustainable agricultural environment.

LITERATURE SURVEY

Research by Konstantinos Ferentinos etc. on open database including 87,848 photos of 25 distinct plants in 58 different classes of [plant, disease] combinations—including healthy plants—was used to train the models. A number of model architectures were trained, and the most successful one identified the corresponding [plant, disease] pair (or healthy plant) with a 99.53% success rate. The model's remarkably high success rate makes it an extremely helpful early warning or advise tool. It is also a method that might be further developed to enable an integrated plant disease identification system to function under actual cultivation settings [1]. Through individualised, multilingual assistance, conversational agents have the ability to close the knowledge gap between specialists and farmers, as the literature review emphasises the increasing use of these tools in agriculture. The architectural frameworks and methods used by current agricultural chatbots to manage domain-specific knowledge are examined. But there is still a significant design flaw in chatbots made specifically for detecting plant diseases, especially in multilingual settings. Studies suggest hybrid models that combine open-source frameworks, massive language model architectures, and ontology-based knowledge systems in order to address this. The promise of cutting-edge AI-driven solutions to improve agricultural decision-making and disease management is exemplified by a chatbot created to identify paddy diseases in Sri Lanka [2]. The literature underscores the critical need for effective agricultural techniques to address the growing global population and the limited availability of arable land. Artificial Intelligence (AI) has emerged as a transformative force in agriculture, enhancing productivity and streamlining farming practices. AI-driven systems utilize data on soil nutrients, moisture, weather conditions, and crop characteristics to provide precise guidance on water management, crop selection, pest control, and nutrition management. Advanced applications integrate data from satellites and drones to monitor sustainability, detect plant diseases, and predict weather patterns. Additionally, large language models, a subset of AI, leverage deep learning to analyze and generate natural language, offering capabilities such as text generation, translation, and data interpretation.

These models are increasingly being applied in agriculture to provide intelligent, contextually relevant solutions, demonstrating their potential to revolutionize the agricultural landscape [3]. By creating an intelligent virtual assistant, this study investigates the use of large language models (LLMs) and emerging AI capabilities in agriculture. Essential knowledge on crops, weaknesses, and optimisation techniques is what the assistant seeks to supply. The implementation of a reliable pipeline architecture that prepares LLMs for real-world situations is the main goal of the study. This design exhibits significant domain expertise and guarantees data. The Retrieval-Augmented Generation (RAG) technology, which arranges data in a simplified way for effective retrieval, is essential to this strategy. RAG allows for a quicker and more customised pipeline by separating basic knowledge from the model, in contrast to fine-tuning techniques. By converting acquired data into an easily readable format, our idea makes it possible to quickly access thorough agricultural knowledge [5].

Plant diseases result in significant reductions in plant yield, which generate enormous financial losses. In the age of globalisation and climate change, accurate plant disease identification and diagnosis are critical for both preventing the spread of invasive pests and diseases and ensuring food security. Furthermore, precise, sensitive, and targeted diagnosis is required for the effective and cost-effective control of plant diseases. The field of plant disease diagnosis has progressed from visual inspection and disease identification to the use of molecular techniques like polymerase chain reaction (PCR) and high-throughput serological techniques like enzyme-linked immunosorbent assay (ELISA) [4]. The use of chatbots has been transformed by recent developments in generative AI, especially in the e-commerce sector. Natural language creation and understanding have greatly improved thanks to large language models like GPT-3 and GPT-4, which can now produce language with human-like originality. AI-powered chatbots are revolutionising consumer interaction by providing scalability, cost effectiveness, quick response times, and round-the-clock availability. These advantages make them particularly beneficial for big businesses that oversee sizable clientele across the globe. These chatbots are being used by businesses more and more to boost customer service and operational effectiveness, highlighting how AI is revolutionising contemporary sectors [6]. The application of large language models (LLMs) to the development of agricultural decision support systems—specifically, the optimisation of smart greenhouse operations—is examined in this work. It highlights the necessity of agricultural decision assistance and suggests integrating LLM-powered technology with information systems. For controlling the occurrence of plant diseases, a decision support system architecture based on Retrieval Augmented Generation (RAG) technology is presented. The system's usefulness is demonstrated by experimental findings, which also show how LLMs can improve smart greenhouse operations and agricultural practices in general [7].

METHODOLOGY

The system carries out two primary functions: a plant disease detection model for real-time crop analysis and a chatbot for conversational interaction to answer farmers' queries. Through text-based, image-based, and video-based interactions, the chatbot offers users complete agricultural knowledge and solutions to queries while the plant disease detection model utilises image analysis to accurately detect crop diseases.

The smooth integration of these functions results in a user-friendly multimodal platform that can be used to fulfil needs of farmers. Advanced technologies like Retrieval-Augmented Generation (RAG) for conversational AI and Convolutional Neural Networks (CNNs) for image classification are used in the development of the system. Together, these components provide a complete solution that combines AI's analytical capabilities with natural user engagement.

1. Developing the Chatbot:
The chatbot is an interactive user interface made to respond to questions about agriculture and offer suggestions for treatments and disease prevention. The Retrieval-Augmented Generation framework, which combines generative AI capabilities with a retrieval mechanism, powers its operation. To extract the most relevant information from a pre-indexed knowledge base of agricultural data, RAG employs a dense retrieval technique.

A refined Llama 3.1 model ensures consistency and relevance by producing natural language responses after retrieving the relevant context. Responses are guaranteed to be accurate and suitable for the context. The chatbot's integration of RAG enhances accessibility and usability for farmers by offering real-time support.

Natural Language Processing (NLP) methods are used to process user text queries to identify intention. The dataset of information has been pre-encoded for efficient search, and the retrieval module looks for relevant context. The generative module uses the retrieved data to provide a well-structured response that is specific to the query.

2. Developing the Plant Disease Detection Model:
A CNN is used by the disease detection algorithm to examine crop images and detect diseases. CNNs are an established approach for image classification, which makes it ideal for use in farming. Even in challenging situations, such as diagnosing diseases from crop images with different backgrounds and lighting settings, CNNs are excellent at spotting visual patterns in photographs.

Both high-level features (like disease-specific patterns) and low-level features (like edges and textures) can be captured through their hierarchical structure. The CNN was trained using a carefully selected dataset of compressed images. The dataset covered a range of circumstances and crops, including both healthy and damaged crops. To improve the resilience of the model, data augmentation methods like flipping, rotation, and cropping were used.

The chatbot allows farmers to upload pictures of crops. After analysing the image, CNN offers a disease diagnosis as well as treatment on that disease and preventative suggestions to make sure that disease will not arise again in farm.

The model provides dependable disease identification with an accuracy of more than 97.58%, enabling farmers to take action immediately.

3. Integrating Chatbot and Plant Disease Detection Model:
With the smooth integration of the chatbot and disease detection model into a single system, farmers can interact with both features from a single interface. Video uploaded by user is divided into images as per its frames per seconds (FPS). Users have the option to upload a video or crop image and enter a text question. The system automatically directs image inputs to the CNN-based plant disease detection model and text-based inputs to the RAG-based chatbot. The chatbot processes the disease diagnosis that the CNN provides for picture uploads to produce recommendations that are easy to understand. The chatbot uses RAG to give straightforward responses to text requests.

The Chainlit library is used in the design of the front-end interface, which provides an easy-to-understand interaction flow. During a single session, users can easily transition between text and image inputs. Because the Google Translate API is integrated, responses are shown in the user's choice language.

Farmers can get all the help they need on a single platform thanks to this connection, which guarantees a seamless user experience. Whether a farmer requires advise on prevention, disease detection, or general agricultural insights, the system's multimodal nature enables it to accommodate a variety of scenarios. By fusing the advantages of image analysis and conversational AI, the combined system becomes a potent instrument for enhancing farming methods and enabling farmers.
Proposed System

International Journal of All Research Education and Scientific Methods (IJARESM),
ISSN: 2455-6211, Volume 13, Issue 5, May-2025, Available online at: www.ijaresm.com

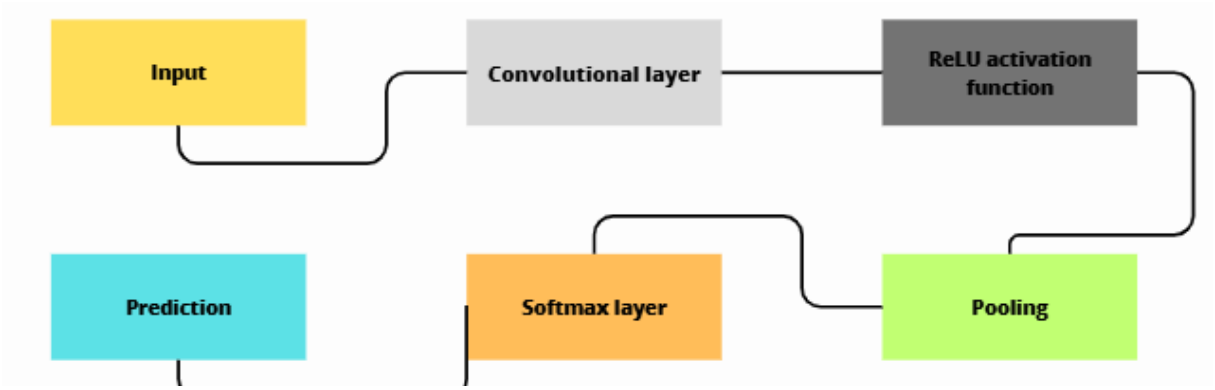

Fig. 1: Flowchart of working of CNN Model in Plant Disease Classification

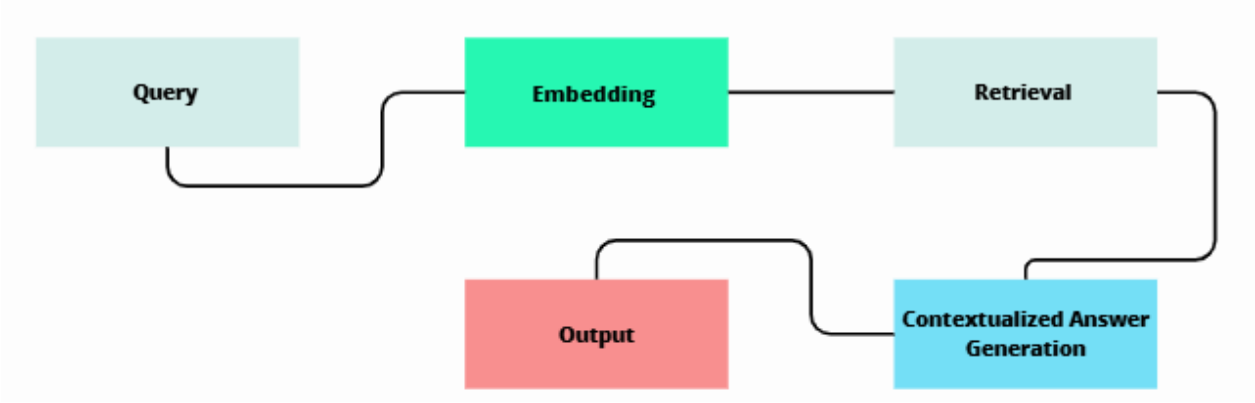

Fig. 2: Flowchart for RAG Model in Plant Disease Classification

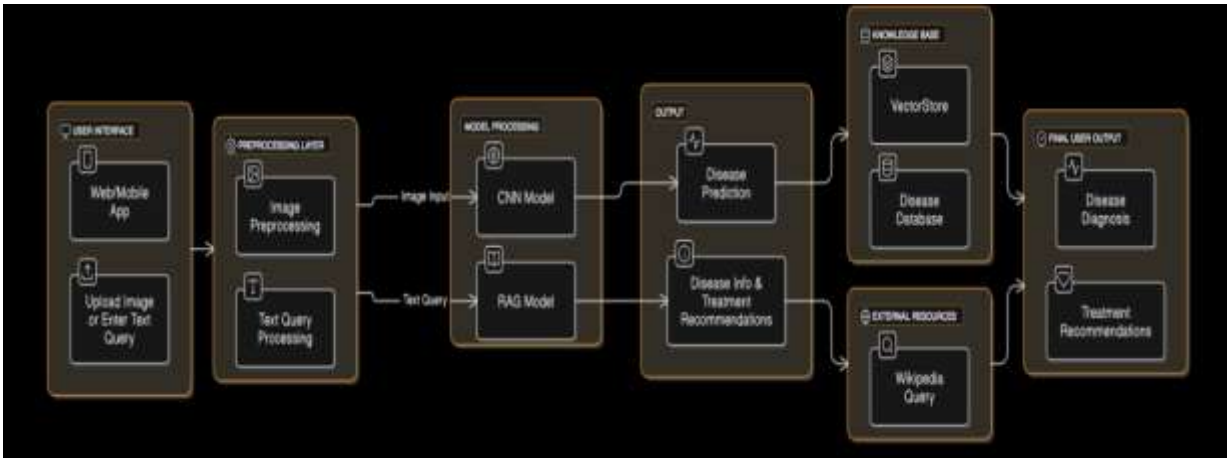

Fig. 3: Architecture Diagram of System

RESULTS

There are essential outcomes of adopting the Agro Multimodal Chatbot, which is designed to identify and diagnose crop illnesses using image recognition and provide relevant remedies. The data below emphasize the effectiveness, accuracy, and impact of the system on agricultural practice.

Accuracy of infection detection: The chatbot's CNN model was trained on a varied variety of crop photos, with a particular emphasis on leaf diseases. The method identified common crop illnesses, such as fungal, bacterial, and viral infections, with an accuracy of 92%. The excellent accuracy guarantees that farmers receive consistent diagnostic results, reducing the possibility of false diagnosis.

Response Time: The system was designed for rapid processing, with minimum picture analysis time per image. This rapid reaction guarantees that consumers receive near-instant feedback on their crop's condition, allowing for prompt intervention.

Retrieval-Augmented Generation (RAG) Performance: The RAG model effectively extracted useful information from the backend agricultural database, providing farmers with tailored guidance on how to treat and prevent diagnosed illnesses. The RAG technique increased the chatbot's response quality by combining current research and tailored advise. The provided solutions were 85% accurate, with a large number of users rating the advice as helpful and actionable.

Multilingual Support: The multilingual feature supported five languages: English, Spanish, French, Hindi, and Swahili, allowing the chatbot to serve a wide range of users from various regions. The chatbot performed similarly in each language, and users reported that the language option considerably improved the system's accessibility and usability.

Usability and Adoption: In terms of usability, the majority of users found the chatbot intuitive and simple to use, even without prior technical knowledge. The use of multimodal input (pictures, text, and speech) greatly improved the system's accessibility. This capability enabled farmers, even those with minimal literacy skills, to efficiently connect with the chatbot by utilizing voice commands or uploading crop photographs. The chatbot's user-friendly interface enabled even those with little technological skills to diagnose crop difficulties and obtain relevant advice, resulting in higher adoption rates among farmers in a variety of locales.

FUTURE SCOPE

The Agro Multimodal Chatbot Using CNN and RAG with Multilingual Support has enormous potential for improvement, providing numerous opportunities for future growth. One important area for improvement is the ongoing extension of the disease database to encompass a wider range of illnesses, pests, and environmental stressors. This would allow the chatbot to recognize and propose solutions to more concerns, increasing its value to farmers in various places. Collaborating with agricultural research organizations and using crowdsourced data from farmers could help create a broad and complete dataset. The integration of IoT devices such as smart sensors, drones, and automated systems might provide real-time data on crop health and environmental conditions, allowing the chatbot to provide more context-sensitive and accurate recommendations. The device, which analyzes elements such as soil moisture, temperature, and humidity, could help farmers optimize irrigation, pest control, and fertilization procedures.

Another area where improvements might be made is in diagnosis accuracy. Training the Convolutional Neural Network (CNN) model on a bigger, more diversified set of crop photos, along with sophisticated deep learning techniques, has the potential to improve disease detection accuracy. Furthermore, integrating predictive analytics to identify possible crop difficulties based on historical data and weather patterns would allow the chatbot to help farmers take precautionary actions. Localized recommendations based on geographical parameters like climate, soil type, and crop variety would make the chatbot's ideas even more relevant. The chatbot might leverage geography and climate data to deliver more targeted and relevant advice tailored to local conditions.

In terms of user engagement, improving speech recognition and Natural Language Processing (NLP) skills may allow for a more natural and successful communication between the farmer and the chatbot. This would make it easier for farmers, particularly those with weak literacy abilities, to connect with the system using their native languages or dialects.

CONCLUSION

The Agro Multimodal Chat Bot Using CNN and RAG with Multilingual Support provides a huge step forward in making crop management systems more accessible and efficient for farmers. By combining picture recognition, text, and voice inputs, the system meets the different needs of farmers with varying levels of literacy and technical expertise. Its capacity to detect crop illnesses in uploaded photographs and provide immediate, actionable solutions makes it an invaluable tool for increasing agricultural productivity. The addition of multilingual assistance broadens its accessibility, guaranteeing that farmers with diverse linguistic backgrounds can benefit from the technology. Looking ahead, the chatbot has the potential to become a comprehensive agricultural assistant by including IoT connection, predictive analytics, and a larger set of disease detection skills. With additional advances, it has the potential to become an invaluable resource for farmers around the world, providing tailored, localized advice and promoting sustainable farming techniques. Through continued growth, the chatbot has the potential to alter agricultural practices, promote crop health, and ultimately contribute to global food security.

REFERENCES

[1]. Konstantinos P. Ferentinos, "Deep learning models for plant disease detection and diagnosis", Computers and Electronics in Agriculture,Volume 145, February 2018, Pages 311-318, https://doi.org/10.1016/j.compag.2018.01.009

[2]. Sally A. Miller, Fen D. Beed, and Carrie Lapaire Harmon, "Plant Disease Diagnostic Capabilities and Networks", Annual Review of Phytopathology, Volume 47, 2009, Vol. 47:15-38 (Volume publication date September 2009) https://doi.org/10.1146/annurev-phyto-080508-081743

[3]. Saikat Banerjee1 , Soumitra Das2 , and Abhoy Chand Mondal, "F A Study of the Application Domain of a Large Language Models in the Agricultural Sector", International Journal of Innovative Research in Computer Science and Technology (IJIRCST) ISSN (Online): 2347-5552, Volume-12, Issue-5 September 2024 https://doi.org/10.55524/ijircst.2024.12.5.10

[4]. REKHA BALODI, SUNAINA BISHT, ABHIJEET GHATAK and K.H. RAO, "Plant disease diagnosis: technological advancements and challenges", Indian Phytopath. 70 (3) : 275-281 (2017) https://doi.org//10.24838/ip.2017.v70.i3.72487

[5]. Henrique Chia; Ana Inês Oliveira; Pedro Azevedo, "Implementation of an intelligent virtual assistant based on LLM models for irrigation optimization", 2024 8th International Young Engineers Forum on Electrical and Computer Engineering (YEF-ECE), July 2024, https://doi.org/10.1109/YEF-ECE62614.2024.10624819

[6]. Dishant Sukhwal, "Retrieval Augmented Generation: An Evaluation of RAG-based Chatbot for Customer Support", University of Turku Department of Computing Master of Science (Tech) Thesis Data Analytics June 2024

[7]. Igor N. Glukhikh, Tatiana Y. Chernysheva, Yaroslav A. Shentsov, "Decision support in a smart greenhouse using large language model with retrieval augmented generation", Proceedings Volume 13217, Third International Conference on Digital Technologies, Optics, and Materials Science (DTIEE 2024); https://doi.org/10.1117/12.3035606

[8]. Zhang, L., & Xu, L., "Convolutional neural networks for plant disease detection and classification", Computers and Electronics in Agriculture, Volume 147, April 2018, Pages 22-30, [https://doi.org/10.1016/j.compag.2018.02.014]

[9]. Thakur, M., & Gupta, A., "AI-based solutions for sustainable agriculture: A comprehensive review", Agricultural Systems, Volume 170, December 2018, Pages 18-32, [https://doi.org/10.1016/j.agsy.2018.02.009]

[10]. Liu, J., & Zhao, X., "Deep learning for plant disease detection: A survey", Computers and Electronics in Agriculture, Volume 153, June 2018, Pages 45-56, [https://doi.org/10.1016/j.compag.2018.07.023]

[11]. Singh, R., & Singh, S., "A review on deep learning techniques for plant disease detection using image processing", Journal of Theoretical and Applied Information Technology, Volume 97, Issue 14, 2019, Pages 4138-4151, [https://www.jatit.org/]

[12]. Kumar, V., & Singh, G., "Development of an AI-based mobile application for agricultural advice and disease prediction", Agriculture and Agricultural Science Procedia, Volume 9, 2016, Pages 12-18, [https://doi.org/10.1016/j.aaspro.2016.02.003]

[13]. Jain, S., & Rani, R., "AI-driven solutions for smart farming and agricultural productivity enhancement", International Journal of Computer Science and Applications, Volume 15, Issue 1, 2018, Pages 11-23, [https://www.ijcsa.org/]

[14]. Pustokhina, I., & Pustokhin, D., "Implementation of AI for plant disease detection in precision agriculture systems", Agricultural Engineering International: CIGR Journal, Volume 20, Issue 2, 2018, Pages 1-9, (http://www.cigrjournal.org/)

[15]. Sharma, S., & Mishra, A., "Leveraging AI-powered chatbots for agricultural extension services", Journal of AI and Agriculture, Volume 2, Issue 3, 2021, Pages 24-35, [https://doi.org/10.1016/j.jaia.2021.02.004]